

Towards AI-Complete Question Answering: A Set of Prerequisite Toy Tasks

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Abstract

One long-term goal of machine learning research is to produce methods that are applicable to reasoning and natural language, in particular building an intelligent dialogue agent. To measure progress towards that goal, we argue for the usefulness of a set of proxy tasks that evaluate reading comprehension via question answering. Our tasks measure understanding in several ways: whether a system is able to answer questions via chaining facts, simple induction, deduction and many more. The tasks are designed to be prerequisites for any system that aims to be capable of conversing with a human. We believe many existing learning systems can currently not solve them, and hence our aim is to classify these tasks into skill sets, so that researchers can identify (and then rectify) the failings of their systems. We also extend and improve the recently introduced Memory Networks model, and show it is able to solve some, but not all, of the tasks.

1. Introduction

There is a rich history of the use of synthetic tasks in machine learning, from the XOR problem which helped motivate neural networks (Minsky & Papert, 1969; Rumelhart et al., 1985), to circle, spiral and ring datasets that helped motivate some of the most well-known clustering and semi-supervised learning algorithms (Ng et al., 2002; Zhu et al., 2003), Mackey Glass equations for time series (Müller et al., 1997), and so on – in fact some of the well known UCI datasets (Bache & Lichman, 2013) are synthetic as well (e.g., *waveform*). Recent work continues this trend. For example, in the area of developing learning algorithms with a memory component synthetic datasets were used to help develop both the Neural Turing Machine of Graves et al. (2014) and the Memory Networks of Weston et al. (2014), the latter of which is relevant to this work.

One of the reasons for the interest in synthetic data is that it can be easier to develop new techniques using it. It is well known that working with large amounts of real data (“big data”) tends to lead researchers to simpler models as “simple models and a lot of data trump more elaborate models based on less data” (Halevy et al., 2009). For example, N -grams for language modeling work well relative to existing competing methods, but are far from being a model that truly understands text. As researchers we can become stuck in local minima in algorithm space; development of synthetic data is one way to try and break out of that.

In this work we propose a framework and a set of synthetic tasks for the goal of helping to develop learning algorithms for text understanding and reasoning. While it is relatively difficult to automatically evaluate the performance of an agent in general dialogue – a long term-goal of AI – it is relatively easy to evaluate responses to input questions, i.e., the task of question answering (QA). Question answering is incredibly broad: more or less any task one can think of can be cast into this setup. This enables us to propose a wide ranging set of different tasks, that test different capabilities of learning algorithms, under a common framework.

Our tasks are built with a unified underlying simulation of a physical world, akin to a classic text adventure game (Montfort, 2005) whereby actors move around manipulating objects and interacting with each other. As the simulation runs, grounded text and question answer pairs are simultaneously generated. Our goal is to categorize *different kinds of questions* into skill sets, which become our tasks. Our hope is that the analysis of performance on these tasks will help expose weaknesses of current models and help motivate new algorithm designs that alleviate these weaknesses. We further envision this as a feedback loop where new tasks can then be designed in response, perhaps in an adversarial fashion, in order to break the new models.

The tasks we design are detailed in Section 3, and the simulation used to generate them in Section 4. In Sec. 6 we give benchmark results of standard methods on our tasks, and analyse their successes and failures. In order to exemplify

the kind of feedback loop between algorithm development and task development we envision, in Section 5 we propose a set of improvements to the recent Memory Network method, which has shown to give promising performance in QA. We show our proposed approach does indeed give improved performance on some tasks, but is still unable to solve some of them, which we consider as open problems.

2. Related Work

Several projects targeting language understanding using QA-based strategies have recently emerged. Unlike tasks like dialogue or summarization, QA is easy to evaluate (especially in true/false or multiple choice scenarios) and hence makes it an appealing research avenue. The difficulty lies in the definition of questions: they must be unambiguously answerable by adult humans (or children), but still require some thinking. The *Allen Institute for AI*'s flagship project ARISTO¹ is organized around a collection of QA tasks derived from increasingly difficult science exams, at the 4th, 8th, and 12th grade levels. Richardson et al. (2013) proposed the *MCTest*², a set of 660 stories and associated questions intended for research on the machine comprehension of text. Each question requires the reader to understand different aspects of the story.

These two initiatives go in a promising direction but interpreting the results on these benchmarks remain complicated. Indeed, no system has yet been able to fully solve the proposed tasks and since many sub-tasks need to be solved to answer any of their questions (coreference, deduction, use of common-sense, etc.), it is difficult to clearly identify capabilities and limitations of these systems and hence to propose improvements and modifications. As a result, conclusions drawn from these projects are not much clearer than that coming from more traditional works on QA over large-scale Knowledge Bases (Berant et al., 2013; Fader et al., 2014). Besides, the best performing systems are based on hand-crafted patterns and features, and/or statistics acquired on very large corpora. It is difficult to argue that such systems actually understand language and are not simply light upgrades of traditional information extraction methods (Yao et al., 2014). The system of (Berant et al., 2014) is more evolved since it builds a structured representation of a text and of a question to answer. Despite its potential this method remains highly domain specific and relies on a lot of prior knowledge.

Based on these observations, we chose to conceive a collection of much simpler QA tasks, with the main objective that failure or success of a system on any of them can unequivocally provide feedback on its capabilities. In that, we are

close to the *Winograd Schema Challenge* (Levesque et al., 2011), which is organized around simple statements followed by a single binary choice question such as: “*Joan made sure to thank Susan for all the help she had received. Who had received the help? Joan or Susan?*”. In this challenge, and our tasks, it is straightforward to interpret results. Yet, where the Winograd Challenge is mostly centered around evaluating if systems can acquire and make use of background knowledge that is not expressed in the words of the statement, our tasks are self-contained and are more diverse. By self-contained we mean our tasks come with both training data and evaluation data, rather than just the latter as in the case of ARISTO, *MCTest* and the Winograd Challenge. In our setup one can assess the amount of training examples needed to perform well. In terms of diversity, some of our tasks are related to existing setups but we also propose many additional ones; tasks 3.8 and 3.9 are inspired by previous work on lambda dependency-based compositional semantics (Liang et al., 2013; Liang, 2013) for instance. For us, each task checks one skill that the system must have and we postulate that performing well on all of them is a prerequisite for any system aiming at full text understanding and reasoning.

3. The Tasks

Our main idea is to provide a set of tasks, in a similar way to how software testing is built in computer science. Ideally each task is a “leaf” test case, as independent from others as possible, and tests in the simplest way possible one aspect of intended behavior. Subsequent (“non-leaf”) tests can build on these by testing combinations as well. The tasks are publicly available at <http://fb.ai/babi>.

Each task provides a set of training and test data, with the intention that a successful model performs well on test data. Following (Weston et al., 2014), the supervision in the training set is given by the true answers to questions, and the set of *relevant* statements for answering a given question, which may or may not be used by the learner. We set up the tasks so that correct answers are limited to a single word (*Q: Where is Mark? A: bathroom*), or else a list of words (*Q: What is Mark holding?*) as evaluation is then clear-cut, and is measured simply as right or wrong.

All of the tasks are noiseless and a human can potentially achieve 100% accuracy. We tried to choose tasks that are natural to a human reader, and no background in areas such as formal semantics, machine learning, logic or knowledge representation is required for an adult to solve them.

The data itself is produced using a simple simulation of characters and objects moving around and interacting in locations, described in Section 4. The simulation allows us to generate data in many different scenarios where the true

¹<http://allenai.org/aristo.html>

²<http://research.microsoft.com/en-us/um/redmond/projects/mctest/>

labels are known by grounding to the simulation. For each task, we describe it by giving a small sample of the dataset including statements, questions and the true labels (in red).

3.1. Basic Factoid QA with Single Supporting Fact

Our first task consists of questions where a single supporting fact that has been previously given provides the answer. We first test one of the simplest cases of this, by asking for the location of a person. A small sample of the task is thus:

John is in the playground.
Bob is in the office.
Where is John? A:playground

This kind of synthetic data was already used in (Weston et al., 2014). It can be considered the simplest case of some real world QA datasets such as in (Fader et al., 2013).

3.2. Factoid QA with Two Supporting Facts

A harder task is to answer questions where two supporting statements have to be chained to answer the question:

John is in the playground.
Bob is in the office.
John picked up the football.
Bob went to the kitchen.
Where is the football? A:playground
Where was Bob before the kitchen? A:office

For example, to answer the first question *Where is the football?*, both *John picked up the football* and *John is in the playground* are supporting facts. Again, this kind of task was already used in (Weston et al., 2014).

Note that, to show the difficulty of these tasks for a learning machine with no other knowledge we can shuffle the letters of the alphabet and produce equivalent datasets:

Sbdm ip im vdu yonrckblms.
Abf ip im vdu bhhigu.
Sbdm yigauss ly vdu hbbvfnoo.
Abf zumv vb vdu aivgdum.
Mduku ip vdu hbbvfnoo? A:yonrckblms
Mduku znp Abf fuhbku vdu aivgdum? A:bhhigu

3.3. Factoid QA with Three Supporting Facts

Similarly, one can make a task with three supporting facts:

John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A:office

The first three statements are all required to answer this.

3.4. Two Argument Relations: Subject vs. Object

To answer questions the ability to differentiate and recognize subjects and objects is crucial. We consider here the extreme case where sentences feature re-ordered words, i.e. a bag-of-words will not work:

The office is north of the bedroom.
The bedroom is north of the bathroom.
What is north of the bedroom? A: office
What is the bedroom north of? A: bathroom

Note that the two questions above have exactly the same words, but in a different order, and different answers.

3.5. Three Argument Relations

Similarly, sometimes one needs to differentiate three separate arguments, such as in the following task:

Mary gave the cake to Fred.
Fred gave the cake to Bill.
Jeff was given the milk by Bill.
Who gave the cake to Fred? A: Mary
Who did Fred give the cake to? A: Bill
What did Jeff receive? A: milk
Who gave the milk? A: Bill

The last question is potentially the hardest for a learner as the first two can be answered by providing the actor that is not mentioned in the question.

3.6. Yes/No questions

This task tests, on some of the simplest questions possible (specifically, ones with a single supporting fact) the ability of a model to answer true/false type questions:

John is in the playground.
Daniel picks up the milk.
Is John in the classroom? A:no
Does Daniel have the milk? A:yes

3.7. Counting

This task tests the ability of the QA system to perform simple counting operations, by asking about the number of objects with a certain property:

Daniel picked up the football.
Daniel dropped the football.
Daniel got the milk.
Daniel took the apple.
How many objects is Daniel holding? A: two

3.8. Lists / Sets

While many of our tasks are designed to have single word answers for simplicity, this set of tasks tests the ability to produce a set of single word answers in the form of a list, by asking about sets of entities with certain properties, e.g.:

Daniel picks up the football.
 Daniel drops the newspaper.
 Daniel picks up the milk.
 What is Daniel holding? **milk, football**

The task above can be seen as a QA task related to a database search operation. Note that we could also consider the following question types: intersection (*Who is in the park carrying food?*), union (*Who has milk or cookies?*) and set difference (*Who is in the park apart from Bill?*). However, we leave those for future work.

3.9. Simple Negation

We test one of the simplest types of negation, that of supporting facts that imply a statement is false:

Sandra travelled to the office.
 Fred is no longer in the office.
 Is Fred in the office? **A:no**
 Is Sandra in the office? **A:yes**

Task 3.6 (yes/no questions) is a prerequisite to this task.

3.10. Indefinite Knowledge

This task tests if we can model statements that describe possibilities rather than certainties:

John is either in the classroom or the playground.
 Sandra is in the garden.
 Is John in the classroom? **A:maybe**
 Is John in the office? **A:no**

3.11. Basic Coreference

This task tests the simplest type of coreference, that of detecting the nearest referent, for example:

Daniel was in the kitchen.
 Then he went to the studio.
 Sandra was in the office.
 Where is Daniel? **A:studio**

Real-world data typically addresses this as a labeling problem and studies more sophisticated phenomena (Haghighi & Klein, 2009). ARISTO also addresses this task.

3.12. Conjunction

This task tests referring to multiple subjects in a single statement, for example:

Mary and Jeff went to the kitchen.
 Then Jeff went to the park.
 Where is Mary? **A: kitchen**

3.13. Compound Coreference

This task tests coreference in the case where the pronoun can refer to multiple actors, for example:

Daniel and Sandra journeyed to the office.
 Then they went to the garden.
 Sandra and John travelled to the kitchen.
 After that they moved to the hallway.
 Where is Daniel? **A: garden**

3.14. Time Manipulation

While our tasks so far have included time implicitly in the order of the statements, this task tests understanding the use of time expressions within the statements, for example:

In the afternoon Julie went to the park.
 Yesterday Julie was at school.
 Julie went to the cinema this evening.
 Where did Julie go after the park? **A:cinema**

Real-world datasets address the task of evaluating time expressions typically as a labeling, rather than a QA, task, see e.g. (UzZaman et al., 2012).

3.15. Basic Deduction

This task tests basic deduction via inheritance of properties:

Sheep are afraid of wolves.
 Cats are afraid of dogs.
 Mice are afraid of cats.
 Gertrude is a sheep.
 What is Gertrude afraid of? **A:wolves**

3.16. Basic Induction

This task tests basic induction via potential inheritance of properties, for example:

Lily is a swan.
 Lily is white.
 Greg is a swan.
 What color is Greg? **A:white**

Clearly, a full analysis of induction is beyond the scope of this work. An answer produced using induction may not be true, which we can control in our simulation.

3.17. Positional Reasoning

This task tests spatial reasoning, one of many components of the classical SHRDLU system (Winograd, 1972):

The triangle is to the right of the blue square.
 The red square is on top of the blue square.
 The red sphere is to the right of the blue square.
 Is the red sphere to the right of the blue square? **A:yes**
 Is the red square to the left of the triangle? **A:yes**

Task 3.6 (yes/no questions) is a prerequisite to this task.

3.18. Reasoning about Size

This task requires reasoning about relative size of objects and is inspired by the commonsense reasoning examples in the Winograd schema challenge (Levesque et al., 2011):

The football fits in the suitcase.
 The suitcase fits in the cupboard.
 The box of chocolates is smaller than the football.
 Will the box of chocolates fit in the suitcase? A: yes

Tasks 3.3 (three supporting facts) and 3.6 (yes/no questions) are prerequisites to this task.

3.19. Path Finding

In this task the goal is to find the path between locations:

The kitchen is north of the hallway.
 The den is east of the hallway.
 How do you go from den to kitchen? A: west, north

This is related to the work of (Chen & Mooney, 2011).

3.20. Reasoning about Agent’s Motivations

This task tries to ask *why* an agent performs a certain action. It addresses the case of actors being in a given state (hungry, thirsty, tired, ...) and the actions they then take:

John is hungry.
 John goes to the kitchen.
 John eats the apple.
 Daniel is hungry.
 Where does Daniel go? A: kitchen
 Why did John go to the kitchen? A: hungry

4. Simulation

All our tasks are generated with a simulation which behaves like a classic text adventure game. The idea is that generating text within this simulation allows us to ground the language used into a coherent and controlled (artificial) world. Our simulation follows those of (Bordes et al., 2010; Weston et al., 2014) but is somewhat more complex.

The simulated world is composed of entities of various types (locations, objects, persons. etc.) and of various actions that operate on these entities. Entities have internal states: their location, if they carry objects on top or inside them (for example tables and boxes), the mental state of actors (e.g. hungry), as well as properties such as size, color, and edibility. For locations, the nearby places that are connected (e.g. what lies to the east, or above) are encoded. For actors a set of pre-specified rules per actor can also be specified to control their behavior, e.g. if they are hungry they may try to find food. Random valid actions can also be executed if no rule is set, e.g. walking around randomly.

The actions an actor can execute in the simulation con-

sist of the following: *go* <location>, *get* <object>, *get* <object1> *from* <object2>, *put* <object1> *in/on* <object2>, *give* <object> *to* <actor>, *drop* <object>, *set* <entity> <state>, *look*, *inventory* and *examine* <object>. A set of universal constraints is imposed on those actions to enforce coherence in the simulation. For example an actor cannot get something that they or someone else already has, they cannot go to a place that is not connected to the current location, cannot drop something they do not already have, and so on.

Using the underlying actions, rules for actors, and their constraints, defines how actors act. For each task we limit the actions needed for that task, e.g. task 3.1 only needs *go* whereas task 3.2 uses *go*, *get* and *drop*. If we write the commands down this gives us a very simple “story” which is executable by the simulation, e.g., *joe go playground; bob go office; joe get football*. This example corresponds to task 3.2. The system can then ask questions about the state of the simulation e.g., *where john?*, *where football?* and so on. It is easy to calculate the true answers for these questions as we have access to the underlying world.

In order to produce more natural looking text with lexical variety from statements and questions we employ a simple automated grammar. Each verb is assigned a set of synonyms, e.g., the simulation command *get* is replaced with either *picked up*, *got*, *grabbed* or *took*, and *drop* is replaced with either *dropped*, *left*, *discarded* or *put down*. Similarly, each object and actor can have a set of replacement synonyms as well, e.g. replacing Daniel with *he* in task 3.11. Adverbs are crucial for some tasks such as the time manipulation task 3.14.

There are a great many aspects of language not yet modeled. For example, all sentences are so far relatively short and contain little nesting. Further, the entities and the vocabulary size is small (150 words, and typically 4 actors, 6 locations and 3 objects used per task). The hope is that defining a set of well defined tasks will help evaluate models in a controlled way within the simulated environment, which is hard to do with real data. These tasks are not a substitute for real data, but should complement them, especially when developing and analysing algorithms. Our aim is to make this simulation more sophisticated and to release improved versions and tasks, over time. Hopefully it can then scale up to evaluate more and more useful properties.

5. Memory Networks

Memory Networks (Weston et al., 2014) are a promising class of models, shown to perform well at QA, that we can apply to our tasks. They consist of a memory \mathbf{m} (an array of objects indexed by \mathbf{m}_i) and four potentially learnable components I , G , O and R that are executed given an input:

- I: (input feature map) – convert input sentence x to an internal feature representation $I(x)$.
- G: (generalization) – update the current memory state \mathbf{m} given the new input: $\mathbf{m}_i = G(\mathbf{m}_i, I(x), \mathbf{m}), \forall i$.
- O: (output feature map) – compute output o given the new input and the memory: $o = O(I(x), \mathbf{m})$.
- R: (response) – finally, decode output features o to give the final textual response to the user: $r = R(o)$.

Potentially, component I can make use of standard pre-processing, e.g., parsing and entity resolution, but the simplest form is to do no processing at all. The simplest form of G is store the new incoming example in an empty memory slot, and leave the rest of the memory untouched. Thus, in (Weston et al., 2014) the actual implementation used is exactly this simple form, where the bulk of the work is in the O and R components. The former is responsible for reading from memory and performing inference, e.g., calculating what are the relevant memories to answer a question, and the latter for producing the actual wording of the answer given O .

The O module produces output features by finding k supporting memories given x . They use $k = 2$. For $k = 1$ the highest scoring supporting memory is retrieved with:

$$o_1 = O_1(x, \mathbf{m}) = \arg \max_{i=1, \dots, N} s_O(x, \mathbf{m}_i) \quad (1)$$

where s_O is a function that scores the match between the pair of sentences x and \mathbf{m}_i . For the case $k = 2$ they then find a second supporting memory given the first found in the previous iteration:

$$o_2 = O_2(q, \mathbf{m}) = \arg \max_{i=1, \dots, N} s_O([x, \mathbf{m}_{o_1}], \mathbf{m}_i) \quad (2)$$

where the candidate supporting memory \mathbf{m}_i is now scored with respect to both the original input and the first supporting memory, where square brackets denote a list. The final output o is $[x, \mathbf{m}_{o_1}, \mathbf{m}_{o_2}]$, which is input to the module R .

Finally, R needs to produce a textual response r . While the authors also consider Recurrent Neural Networks (RNNs), their standard setup limits responses to be a single word (out of all the words seen by the model) by ranking them:

$$r = R(q, w) = \operatorname{argmax}_{w \in W} s_R([x, \mathbf{m}_{o_1}, \mathbf{m}_{o_2}], w) \quad (3)$$

where W is the set of all words in the dictionary, and s_R is a function that scores the match.

The scoring functions s_O and s_R have the same form, that of an embedding model:

$$s(x, y) = \Phi_x(x)^\top U^\top U \Phi_y(y). \quad (4)$$

where U is a $n \times D$ matrix where D is the number of features and n is the embedding dimension. The role of Φ_x and Φ_y is to map the original text to the D -dimensional feature space. They choose a bag of words representation, and $D = 3|W|$ for s_O , i.e., every word in the dictionary has three different representations: one for $\Phi_y(\cdot)$ and two for $\Phi_x(\cdot)$ depending on whether the words of the input arguments are from the actual input x or from the supporting memories so that they can be modeled differently.

They consider various extensions of their model, in particular modeling write time and modeling unseen words. Here we only discuss the former which we also use. In order for the model to work on QA tasks over stories it needs to know which order the sentences were uttered which is not available in the model directly. They thus add extra write time extra features to S_O which take on the value 0 or 1 indicating which sentence is older than another being compared, and compare triples of pairs of sentences and the question itself. Training is carried out by stochastic gradient descent using supervision from both the question answer pairs and the supporting memories (to select o_1 and o_2). See (Weston et al., 2014) for more details.

5.1. Shortcomings of the Existing MemNNs

The Memory Networks models defined in (Weston et al., 2014) are one possible technique to try on our tasks, however there are several tasks which they are likely to fail on:

- They model sentences with a bag of words so are likely to fail on tasks such as the 2-argument (Sec. 3.4) and 3-argument (Sec. 3.5) relation problems.
- They perform only two max operations ($k = 2$) so they cannot handle questions involving more than two supporting facts such as tasks 3.3 and 3.7.
- Unless a RNN is employed in the R module, they are unable to provide multiple answers in the standard setting using eq. (3). This is required for the list (3.8) and path finding (3.19) tasks.

We therefore propose improvements to their model in the following section.

5.2. Improving Memory Networks

5.2.1. ADAPTIVE MEMORIES (AND RESPONSES)

We consider a variable number of supporting facts that is automatically adapted dependent on the question being asked. To do this we consider scoring a special fact m_\emptyset . Computation of supporting memories then becomes:

```

i = 1
o_i = O(x, m)
while o_i ≠ m_∅ do
    i ← i + 1
    
```

Table 1. Test accuracy (%) on our 20 Tasks for various methods (training with 1000 training examples on each). Our proposed extensions to MemNNs are in columns 5-9: with adaptive memory (AM), N -grams (NG), nonlinear matching function (NL), multilinear matching (ML), and combinations thereof. Bold numbers indicate tasks where our extensions achieve $\geq 95\%$ accuracy but the original MemNN model of (Weston et al., 2014) did not. The last two columns (10-11) give extra analysis of the $\text{MemNN}_{AM+NG+NL}$ method. Column 10 gives the amount of training data for each task needed to obtain $\geq 95\%$ accuracy, or *FAIL* if this is not achievable with 1000 training examples. The final column gives the accuracy when training on all data at once, rather than separately.

TASK	N -grams	LSTM	MemNN (Weston et al., 2014)	MemNN ADAPTIVE MEMORY	MemNN AM + N-GRAMS	MemNN AM + NONLINEAR	MemNN AM + MULTILINEAR	MemNN AM + NG + NL	No. of ex. req. ≥ 95	MultiTask Training
3.1 - Single Supporting Fact	36	50	100	100	100	100	100	100	250 ex.	100
3.2 - Two Supporting Facts	2	20	100	100	100	100	100	100	500 ex.	100
3.3 - Three Supporting Facts	7	20	20	100	99	100	99	100	500 ex.	98
3.4 - Two Arg. Relations	50	61	71	69	100	73	100	100	500 ex.	80
3.5 - Three Arg. Relations	20	70	83	83	86	86	98	98	1000 ex.	99
3.6 - Yes/No Questions	49	48	47	52	53	100	100	100	500 ex.	100
3.7 - Counting	52	49	68	78	86	83	90	85	FAIL	86
3.8 - Lists/Sets	40	45	77	90	88	94	91	91	FAIL	93
3.9 - Simple Negation	62	64	65	71	63	100	100	100	500 ex.	100
3.10 - Indefinite Knowledge	45	44	59	57	54	97	96	98	1000 ex.	98
3.11 - Basic Coreference	29	72	100	100	100	100	100	100	250 ex.	100
3.12 - Conjunction	9	74	100	100	100	100	100	100	250 ex.	100
3.13 - Compound Coreference	26	94	100	100	100	100	100	100	250 ex.	100
3.14 - Time Reasoning	19	27	99	100	99	100	99	99	500 ex.	99
3.15 - Basic Deduction	20	21	74	73	100	77	100	100	100 ex.	100
3.16 - Basic Induction	43	23	27	100	100	100	100	100	100 ex.	94
3.17 - Positional Reasoning	46	51	54	46	49	57	60	65	FAIL	72
3.18 - Size Reasoning	52	52	57	50	74	54	89	95	1000 ex.	93
3.19 - Path Finding	0	8	0	9	3	15	34	36	FAIL	19
3.20 - Agent's Motivations	76	91	100	100	100	100	100	100	250 ex.	100
Mean Performance	34	49	75	79	83	87	93	93		92

$o_i = O([x, m_{o_1}, \dots, m_{o_{i-1}}], \mathbf{m})$
end while

That is, we keep predicting supporting facts i , conditioning at each step on the previously found facts, until m_\emptyset is predicted at which point we stop. m_\emptyset has its own unique embedding vector, which is also learned. In practice we still impose a hard maximum number of loops in our experiments to avoid fail cases where the computation never stops (in our experiments we use a limit of 10).

Multiple Answers We use a similar trick for the response module as well in order to output multiple words. That is, we add a special word w_\emptyset to the dictionary and predict word w_i on each iteration i conditional on the previous words, i.e., $w_i = R([x, m_{o_1}, \dots, m_{|o|}, w_i, \dots, w_{i-1}], w)$, until we predict w_\emptyset .

5.2.2. NONLINEAR SENTENCE MODELING

There are several ways of modeling sentences that go beyond a bag-of-words, and we explore three variants here. The simplest is a bag-of- N -grams, we consider $N = 1, 2$ and 3 in the bag. The main disadvantage of such a method is that the dictionary grows rapidly with N . We therefore

consider an alternative neural network approach, which we call a **multilinear** map. Each word in a sentence is binned into one of P_{sz} positions with $p(i, l) = \lceil (iP_{sz})/l \rceil$ where i is the position of the word in a sentence of length l , and for each position we employ a $n \times n$ matrix $P_{p(i,l)}$. We then model the matching score with:

$$s(q, d) = E(q) \cdot E(d); \quad E(x) = \tanh\left(\sum_{i=1, \dots, l} P_{p(i,l)} \Phi_x(x_i)^\top U\right) \quad (5)$$

whereby we apply a linear map for each word dependent on its position, followed by a \tanh nonlinearity on the sum of mappings. Note that this is related to the model of (Yu et al., 2014) who consider tags rather than positions.

Finally, to assess the performance of nonlinear maps that do not model word position at all we also consider the following **nonlinear** embedding:

$$E(x) = \tanh(W \tanh(\Phi_x(x)^\top U)). \quad (6)$$

where W is a $n \times n$ matrix. This is similar to a classical two-layer neural network, but applied to both sides q and d of $s(q, d)$. We also consider the straight-forward combination of bag-of- N -grams followed by this nonlinearity.

6. Experiments

We compared the following methods on our set of tasks: (i) an N -gram baseline, (ii) LSTMs (long short term memory Recurrent Neural Networks) (Hochreiter & Schmidhuber, 1997), (iii) Memory Networks (MemNNs); and (iv) our extensions of Memory Networks described in Section 5.2. The N -gram baseline is inspired by the baselines in (Richardson et al., 2013) but applied to the case of producing a 1-word answer rather than a multiple choice question: we construct a bag-of- N -grams for all sentences in the story that share at least one word with the question, and then learn a linear classifier to predict the answer using those features³. LSTMs are a popular method for sequence prediction and outperform standard RNNs for similar tasks to ours in (Weston et al., 2014). Note that they are supervised by answers only, not supporting facts, and are hence at a disadvantage compared to MemNNs which use them⁴.

For each task we use 1000 questions for training, and 1000 for testing. Learning rates and other hyperparameters are chosen using the training set. For all MemNN variants we fixed the embedding dimension to $n = 50$ for simplicity, however evaluation with larger n gave similar results.

The summary of our experimental results on the tasks is given in Table 1. We give results for each of the 20 tasks separately and the mean performance in the final row.

Standard MemNNs generally outperform the N -gram and LSTM baselines, which is consistent with the results in (Weston et al., 2014). However they still “fail” at a number of tasks; that is, as the tasks have been built such that they are noise-free we define failure to be test accuracy less than 95%⁵. Some of these failures are expected as stated in Sec. 5.1, e.g. $k = 2$ facts, single word answers and bag-of-words do not succeed on tasks 3.3, 3.4, 3.5, 3.7, 3.8 and 3.18. However, there were also failures on tasks we did not at first expect, for example yes/no questions (3.6) and indefinite knowledge (3.10). Given hindsight, we realize that the linear scoring function of standard MemNNs cannot model the match between query, supporting fact and a yes/no answer as this requires three-way interactions.

Columns 5-9 of Table 1 give the results for our MemNN extensions: adaptive memories and responses (AM) of Sec. 5.2.1, and the three sentence modeling approaches of Sec. 5.2.2: N -grams (NG), multilinear (ML) and nonlinear (NL), plus combinations thereof. The adaptive approach

gives a straight-forward improvement in tasks 3.3 and 3.16 because they both require more than two supporting facts, and also gives (small) improvements in 3.8 and 3.19 because they require multi-word outputs (but still remain difficult). We hence use the AM model in combination with all our other extensions in the subsequent experiments.

MemNNs with N -gram modeling yield clear improvements when word order matters, e.g. tasks 3.4 and 3.15. However, N -grams do not seem to be a substitute for non-linearities in the embedding function as the NL model outperforms N -grams on average, especially in the yes/no (3.6) and indefinite tasks (3.10), as explained before. On the other hand, the NL method cannot model word order and so fails e.g., on task 3.4. The obvious step is thus to combine these complimentary approaches: indeed AM+NG+NL (column 9) gives improved results over both, with a total of 9 tasks that have been upgraded from failure to success compared to the original MemNN model. The multilinear model, as an alternative to this approach, also does similarly well and may be useful in real-world cases where N -grams cause the dictionary to be too large.

The final two columns (10-11) give further analysis of the AM+NG+NL MemNN method. The second to last column (10) shows the minimum number of training examples required to achieve $\geq 95\%$ accuracy, or *FAIL* if this is not achieved with 1000 examples. This is important as it is not only desirable to perform well on a task, but also using the fewest number of examples (to generalize well, quickly). Most tasks require 100-500 examples. Task 3.8 requires 5000 examples and 3.7 requires 10000, hence they are labeled as *FAIL*. The latter task can presumably be solved by adding all the times an object is picked up, and subtracting the times it is dropped, which seems possible for an MemNN, but it does not do perfectly. Two tasks, positional reasoning 3.17 and path finding 3.19 cannot be solved even with 10000 examples, it seems those (and indeed more advanced forms of induction and deduction, which we plan to build) require a general search algorithm to be built into the inference procedure, which MemNN are lacking.

The last column shows the performance of AM+NG+NL MemNNs when training on *all* the tasks jointly, rather than just on a single one. The performance is generally encouragingly similar, showing such a model can learn many aspects of text understanding and reasoning simultaneously.

7. Conclusion

We developed a set of tasks that we believe are a prerequisite to full language understanding and reasoning, and presented some interesting models for solving some of them. While any learner that can solve these tasks is not necessarily close to solving AI, we believe if a learner fails on any of our tasks it exposes it is definitely *not* going to solve AI.

³Constructing N -grams from all sentences rather than using the filtered set gave worse results.

⁴It may be clearer to evaluate models in two tracks: fully and weakly supervised. Weak supervision is ultimately desirable; full supervision gives accuracy upper bounds for “weak” models.

⁵The choice of 95% (and 1000 training examples) is arbitrary.

Overall, our experiments give further proof that Memory Networks are an interesting model beyond the original paper. However, we also highlighted many flaws in that model, which our proposed extensions ameliorate to a degree.

We hope that future research will aim to minimize the amount of required supervision, as well as the number of training examples that has to be seen to solve a new task. For example, it seems that humans are able to generalize to new tasks after seeing only couple of dozen of examples, without having any additional supervision signal. Further, our hope is that a feedback loop of developing more challenging tasks, and then algorithms that can solve them, leads us in a fruitful research direction.

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